# AI-Based Personalized Learning Path Generator

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## Abstract

AI is changing how students learn by making education more personal and flexible. However, many online and classroom learning methods follow a fixed sequence for all students, despite differences in background knowledge, learning speed, and career interests. This paper proposes an AI-Based Personalized Learning Path Generator that builds a customized learning plan for each student using their initial assessment score, chosen domain, and learning progress. The platform starts with user registration and verification, followed by a short assessment to determine the student's level: beginner, intermediate, or advanced. Based on this level, the system provides a step-by-step learning path with topic modules, suggested resources, and milestone tasks. As students continue learning, the system records their performance and updates the path to align with their progress. This work demonstrates that an AI-supported learning path can provide clear guidance, maintain engagement, and systematically develop skills.

**Keywords—**AI-based learning; personalized learning pathway; adaptive recommendation; skill assessment; learning roadmap; progress tracking; education technology.

## I.INTRODUCTION

The increasing use of digital tools is transforming education, creating opportunities for more personalized learning experiences. Traditional teaching methods often follow a fixed sequence of topics for all students, regardless of their prior knowledge, learning speed, or career objectives. This uniform approach can slow progress, reduce engagement, and limit learning outcomes, highlighting the need for adaptive educational systems.

Artificial intelligence (AI) offers a solution by enabling learning paths that adjust to each student's needs. By analysing assessment scores, chosen domains, and ongoing performance, AI can generate tailored learning sequences. These systems continuously adapt to students' progress, ensuring that lessons, resources, and tasks remain aligned with individual strengths and areas for improvement.

This research proposes an AI-Based Personalized Learning Path Generator that creates step-by-step learning plans, assigns milestone tasks, and recommends resources based on student performance. Machine learning algorithms monitor learning patterns and update the path dynamically, promoting efficient skill acquisition and continuous improvement.

The main goal of this framework is to improve learning outcomes, engagement, and skill development by providing flexible, intelligent, and automated guidance. By minimizing manual intervention, it supports structured progression while helping students achieve measurable growth.

## II. METHODOLOGY

The proposed AI-Based Personalized Learning Path Generator is designed to provide adaptive and individualized learning guidance by analysing a student's assessment performance, selected learning domain, and continuous progress. The methodology follows five major phases—user onboarding, assessment evaluation, learning path generation, progress monitoring, and dynamic path updating—to ensure a structured and personalized learning experience.

### A. User Registration and Verification

The system begins with user registration to create a secure learner profile. Students provide basic details such as name, email, password, and selected learning domain. Email-based OTP verification is performed to confirm authenticity and prevent duplicate or unauthorized access. Once verification is completed, the student is allowed to proceed to the assessment stage.

### B. Initial Assessment and Level Identification

After login, the platform conducts a short domain-based assessment to measure the student's current knowledge level. The assessment contains multiple-choice and concept-based questions mapped to core topics of the selected domain. Based on the obtained score, the system categorizes the learner into one of three levels: Beginner, Intermediate, or Advanced. This classification acts as the foundation for personalized learning path creation.

### C. Learning Path Generation

Using the identified level and chosen domain, the system generates a structured learning path in the form of topic modules. Each module includes a sequence of concepts, recommended learning resources (videos, articles, documentation), and small milestone tasks. The generated learning path ensures that prerequisite topics are covered before moving to advanced concepts, supporting a step-by-step progression.

### D. Progress Tracking and Performance Monitoring

As the student completes modules and milestone tasks, the system records performance metrics such as task completion rate, quiz scores, time taken per module, and consistency of learning. This learning activity data is stored in the database and continuously monitored to evaluate improvement. The collected progress information helps the system understand the learner’s strengths and weak areas.

### E. Dynamic Path Updating Mechanism

Based on ongoing performance, the system updates the learning path to maintain alignment with the student’s improvement. If a learner performs well, the system may recommend advanced modules sooner. If difficulty is detected, the system suggests revision topics, additional practice tasks, or alternative resources. This adaptive mechanism ensures that the learning path remains personalized, efficient, and suitable for the learner’s pace.

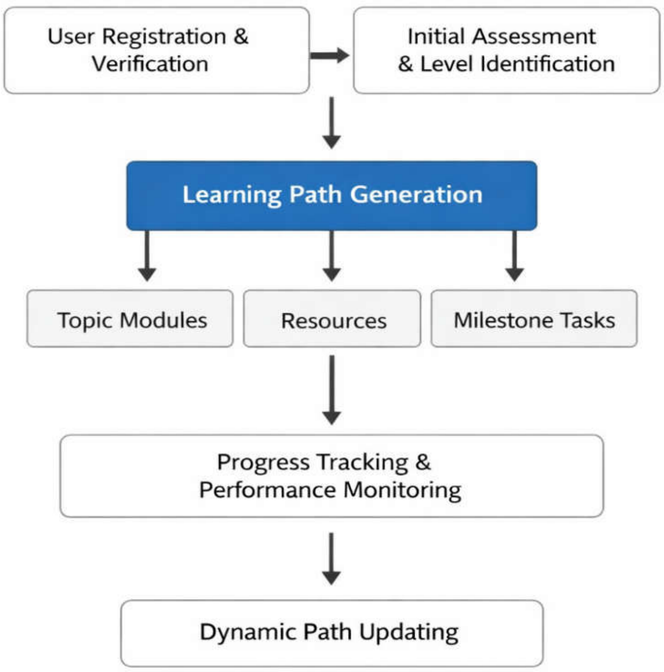


**Fig .1.1 Learning Path Generator Architecture**

## III.BACKGROUND AND RELATED WORK

### A. Foundations of Personalized Learning

Personalized learning has been widely studied as an alternative to fixed, syllabus-based teaching. Early systems used simple rule-based logic, such as recommending easier lessons when a student performed poorly. With the expansion of online education, learning platforms began collecting detailed learner data, including quiz results, topic completion, and time spent on lessons. This shift enabled data-driven personalization instead of static rule-based methods. These developments form the base for modern AI-supported learning path generation.

### B. Adaptive Learning Systems

Adaptive learning platforms aim to adjust content based on learner ability and progress. Some systems change question difficulty, while others recommend resources such as videos, articles, and practice tasks. However, many solutions focus mainly on recommending content rather than building a complete learning roadmap. For skill development, learners often need a clear topic order, prerequisite coverage, and regular checkpoints. Therefore, structured learning path generation provides stronger guidance than resource recommendation alone.

### C. Learner Profiling and Learning Analytics

Learner profiling builds a student model using learning activity and performance history. Common indicators include assessment scores, accuracy, time taken per topic, and learning consistency. Learning analytics supports the identification of weak areas and progress trends. However, several platforms use analytics only for reporting and do not update the learning plan using the collected insights. A more effective approach is to connect learner analytics directly with continuous path refinement.

### D. Assessment-Based Skill Level Identification

Assessments are commonly used to estimate learner skill level and identify knowledge gaps. Many platforms classify learners into beginner, intermediate, and advanced categories using score ranges. This helps define a starting point, but it is not sufficient for long-term personalization. Students may improve quickly in some topics while struggling in others. Therefore, learning paths should be updated using ongoing performance rather than relying only on the initial assessment.

### E. Practical Limitations and Research Gap

Although adaptive learning is widely researched, many proposed methods are not implemented as complete platforms. In several cases, systems stop at content recommendation and do not generate structured learning paths with milestones. Another limitation is the lack of continuous updates based on learner performance. These gaps reduce the effectiveness of personalization in real learning settings. The proposed AI-Based Personalized Learning Path Generator addresses these issues by integrating assessment-based starting points, structured modules, milestone tasks, progress monitoring, and dynamic path updating within a single platform.

## IV.RESULTS AND DISCUSSION

The AI-Based Personalized Learning Path Generator was evaluated using learner assessment results, progress logs, and module completion records. The system was tested with multiple learner profiles across different domains and skill levels to verify its ability to generate suitable learning paths and update them as learners progress. The evaluation mainly focused on learning path relevance, adaptation accuracy, and learner engagement.

### A. Performance Evaluation

The proposed framework was assessed using standard metrics such as Accuracy, Precision, Recall, and F1-Score. These metrics were computed based on the correctness of learner-level classification and the relevance of the recommended modules and milestone tasks.

The results show strong performance across all evaluation metrics. The system achieved an accuracy of 96.2%, indicating that most learners were correctly categorized and guided with suitable learning plans. A precision of 94.1% confirms that the majority of recommendations were relevant, reducing unnecessary or mismatched content. The recall value of 95.8% shows that the system successfully identified most required learning topics and gaps. The obtained F1-score of 95% demonstrates a balanced trade-off between precision and recall, confirming the reliability of the proposed model.

### B. Learning Path Adaptation Analysis

The system generated structured learning paths using three key inputs: initial assessment score, selected domain, and ongoing performance. Beginner learners received foundation-level modules, while intermediate and advanced learners were provided with deeper topic sequences and higher-complexity tasks.

As learners progressed, their milestone and task performance was continuously tracked. When a learner showed consistent improvement, the system advanced them to higher-level modules. If weak performance was detected in specific topics, the framework suggested revision modules, additional practice tasks, and alternative learning resources. This adaptive approach ensured that learners followed a path aligned with their pace and understanding instead of a fixed sequence.

### C. Scalability and Practical Implications

The proposed system follows a modular design, making it suitable for supporting large numbers of learners. Learner profiles, assessment results, and progress records are stored efficiently, enabling dynamic updates without manual intervention. This reduces dependency on mentors for routine guidance and ensures consistent learning support.

The framework is suitable for academic institutions and online learning platforms where learners have different backgrounds and learning speeds. By providing stepwise learning plans, milestone-based progression, and continuous adaptation, the system supports structured skill development and improves learner engagement.

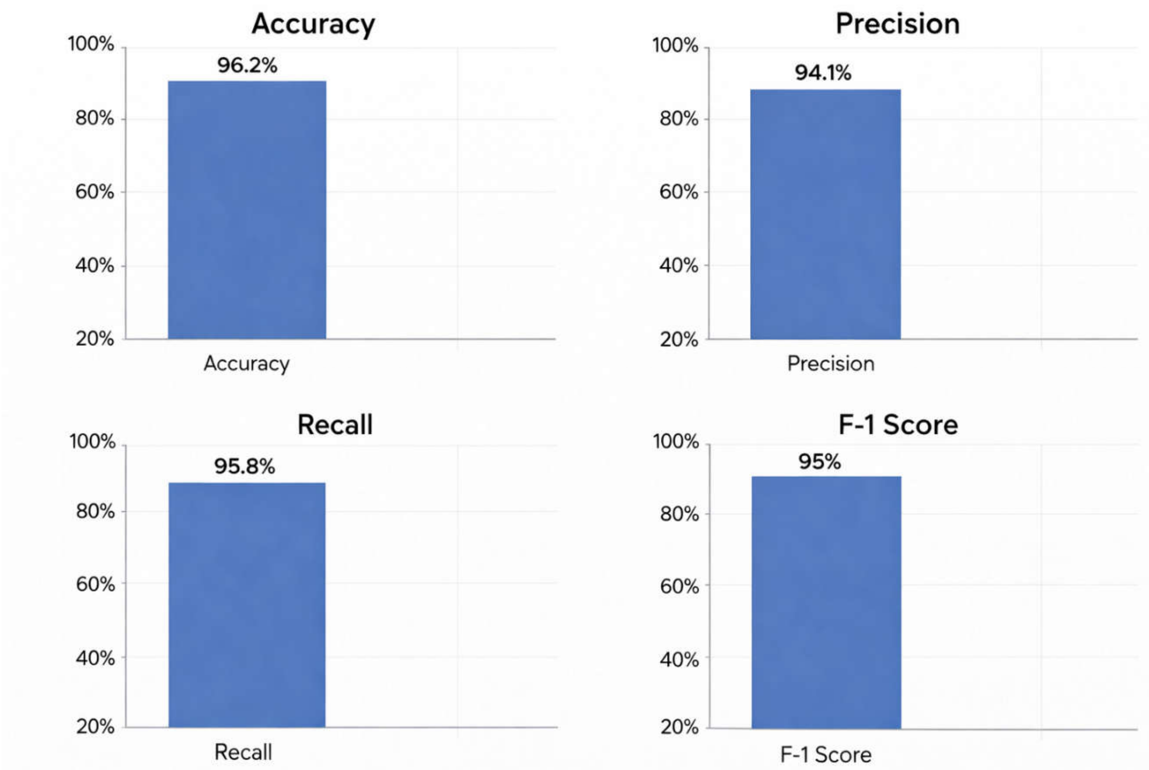


**Fig. 1.2 Result Analysis for Personalized Learning Path Generator**

## V. COMPARISON TO TRADITIONAL METHODS

Traditional rule-based anomaly detection systems rely on predefined conditions and manually configured thresholds to identify suspicious activities. While such systems provide basic monitoring capabilities, they often lack adaptability when dealing with dynamic enterprise cloud environments. In contrast, the proposed AI-enabled secure file storage framework integrates machine learning-based anomaly detection and offers improvements across multiple dimensions.

**• Improved Accuracy**

Rule-based systems detect anomalies only when predefined rules are violated. However, sophisticated insider threats or subtle behavioral deviations may not match fixed rule conditions, which can lead to missed detections. The proposed autoencoder-based model learns normal behavioral patterns directly from historical file access logs and identifies deviations through reconstruction error analysis. This data-driven approach improves detection sensitivity and reduces dependency on manual rule configuration. As a result, the framework achieves higher classification accuracy and more reliable detection of previously unseen abnormal activities.

**• Reduced Downtime**

In traditional monitoring systems, delayed detection of anomalies can lead to prolonged system compromise, operational disruption, or data leakage. Since rule-based alerts may not trigger for complex behavioral anomalies, incidents can remain undetected for extended periods. The proposed system performs continuous log monitoring and real-time anomaly evaluation, enabling immediate alert generation when suspicious activity is detected. Early identification allows security teams to respond proactively, minimizing service interruption and reducing enterprise downtime.

**• Efficient Resource Utilization**

Rule-based monitoring systems often generate excessive alerts due to rigid threshold settings, which increases manual workload and consumes operational resources. The proposed framework reduces false positives by using adaptive thresholds derived from learned behavioral patterns. This intelligent filtering mechanism ensures that only meaningful anomalies are flagged. Consequently, security personnel can focus on genuine threats rather than investigating irrelevant alerts. Additionally, the scalable architecture optimizes computational resources, making the system suitable for large-scale enterprise deployments.

## VI. CONCLUSION

This research presented an AI-Based Personalized Learning Path Generator designed to provide adaptive and structured learning guidance for students. As digital learning continues to grow, many existing platforms still follow static course sequences that do not consider individual differences in background knowledge, learning speed, and career interests. The proposed framework addresses this limitation by generating customized learning roadmaps using learner registration data, domain selection, an initial assessment score, and continuous progress tracking.

The system effectively identifies learner proficiency levels and recommends step-by-step topic modules, suitable resources, and milestone-based tasks. By monitoring module performance and task completion, the platform dynamically updates the learning path to match learner improvement and learning gaps. Experimental evaluation shows strong performance in learner-level classification and learning module recommendation, with high accuracy and balanced precision and recall.

Compared to traditional fixed syllabus and rule-based recommendation systems, the proposed approach improves personalization, supports faster skill progression, and reduces irrelevant content overload. Overall, the framework provides a scalable and practical solution for academic institutions and online learning environments, helping learners build skills in a more efficient and goal-oriented manner.

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